Department of Economics

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Assessing the Role of Fatigue and Task Switching on Worker Performance. Evidence from MLB Pitchers.

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Abstract

Opportunities to study how workers respond to the demands of task switching outside of a laboratory setting are rare. In this paper, we use three seasons of (pre Covid) Major League Baseball (MLB) data to see how pitchers are affected by the additional demands of having to bat and run bases. MLB is an ideal setting because of its two-league structure in which the American League has a Designated Hitter rule, allowing teams to nominate a player to bat in place of the pitcher. The National League does not (or did not, pre Covid). We assess changes to a host of performance metrics, and results suggest that task switching in the form of batting is associated with gains across most of our performance measures, but that pitchers should avoid getting on base at all costs. This finding is robust to within game and across league selection of pitchers, and to a placebo test.

Keywords: Labour Productivity, Task Switching, Baseball
JEL Classification: J24, M54, Z21, Z22

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Declarations
A version of this work was included in Alex Farnell's thesis. No conflicts of interests declared.

1. Introduction

Managers should be greatly interested in how fatigue affects the productivity of workers. Over the course of a working day, for example, workers may become mentally and / or physically fatigued, possibly leading to a loss in productivity. Hart (2004) proposes that the marginal productivity of hours worked varies over the course of the working day. In fact, at the start of the day it could be that marginal productivity actually rises as workers are "warming-up", but eventually fatigue or boredom sets in and productivity falls.

One possible source of fatigue comes from the requirement for workers to carry out multiple tasks (see for example Russ and Crews (2014)). Most, if not all jobs, as well as other daily activities such as household production (Kalenkoski & Foster (2015)) involve some degree of switching between different tasks. These may be job related (checking work emails, attending meetings, meeting clients etc.) or not (checking mobile phones, checking sports news etc.). But changing tasks is likely to involve switching costs, perhaps in the form of a mental adjustment to adapt to a new task, or through lost productive time when switching tasks. Indeed, a body of literature from psychology and behavioural economics (for example Buser and Peter (2012)) suggests subjects tend to struggle when faced with such demands.

However, there has been little in the way of empirical research from natural settings to understand how task switching effects productivity and performance. This, in part, is due to the lack of detailed worker level productivity data, since it can be difficult to define productivity in many occupations. Even if accurate productivity measures are available, it is rare to observe them on a frequent enough basis to track changes over short spaces of time. To address these shortcomings in measurement, we use a particularly rich micro-level dataset containing accurate and comparable measures of worker performance and indicators of task switching. The industry is professional baseball, Major League Baseball (MLB), and the workers under consideration are starting pitchers. Economists have often turned to sports as a way of overcoming data limitations, and with good reason. As Papps (2020) puts it, sports allows researchers to measure typically unobserved factors, and even features that one may assume are unique to the sports labour market (earnings inequality, monitoring of effort etc.) often emerge in the general labour market decades later.

Pitching involves a great level of physical exertion, and so the cumulative effect of pitching over the course of a game will likely impede a pitcher's ability to perform. Indeed, we show that there is a general decline in performance over the course of a game as measured by velocity, command, and walks and runs given up. Of note for this study on task switching is the two-league structure of MLB. The American League has a so called "Designated Hitter Rule", meaning that one player, usually the pitcher, is exempt from batting and a "Designated Hitter" takes their spot in the batting order. Whereas in the National League, pitchers must bat, and if successful at bat, run bases too. Our identification strategy relies on the fact that pitchers can be observed playing in both leagues because of interleague play, and thus the same pitchers are exposed to treatment and control games throughout a season. Pitchers are specialists who have built a career based on their pitching. Batting and running bases are outside of their main skill set, so it is conceivable that these activities could impede their ability to carry out their primary role of pitching.

Contrary to expectations, however, we find a largely positive effect of previously batting, with gains to velocity, and crucially, giving up fewer runs to the opposition. However, for those pitchers who have a successful at bat and get on base, their subsequent pitching performance declines. In other words, pitchers should stay active between innings (batting), but to no get too fatigued (running bases), a result that we believe, but without being able to test, highlights a distinction between mental and physical fatigue. Results hold when testing the robustness of our results against pitcher selection and ability, and when subjected to a placebo check.

The remainder of the paper is structured as follows. Section 2 offers a review of the literature on the effects of fatigue and task switching on productivity. Section 3 offers an overview of baseball and MLB. Section 4 describes the data and measures of task switching in our setting, followed by an overview of the model to be estimated in Section 5. Section 6 presents the results with and Section 7 concludes our work by discussing implications of these findings and where results may lie with respect to other labour markets.

2. Theory & Literature Review

We contribute to a number of strands of literature with a particular focus on the effects of fatigue and task switching on performance. Even though our focus is on baseball, we believe our findings are generalizable not only to other sports, but also to more general labour market settings, particularly jobs that involve carrying out physical tasks.

2.1 Fatigue

Work examining the effects of fatigue on performance tends to focus on the association between hours worked and output. For example, Pencavel (2015) considers the case of munition factory workers during the First World War in Britain. In this setting, exogenous variation in hours worked was largely driven by the demand for shells on the front line. He finds that up to about 48 hours of work per week, the rise in output was proportional to hours worked, but working beyond this this point causes the marginal product of hours to diminish, with maximum output being achieved at about 63 hours. Collewet and Sauermann (2017) also uncover diminishing marginal productivity of hours for workers in a Dutch call centre. For a 1% increase in hours worked, output only rose by 0.9%. The effect remained significant even when controlling for employee and shift characteristics (e.g. shorter night or weekend shifts, and hence more productive shifts), though the magnitude of the effects fell somewhat.

Not all research, however, finds evidence of this negative association. In fact, Lu and Lu (2017) find the opposite to be true. Their Difference in Differences strategy uses state variations in the abolishment of mandatory overtime for nurses in nursing homes. They find that the number of deficiency citations (a measure of poor service quality) increased by almost 22% in treated states, though this change was not related to fatigue and instead related to changes in staffing composition, with nursing homes decreasing the hours of permanent staff and increasing the hours of contract nurses. Crocker and Horst (1981) found no evidence of a decline in marginal value product (measured by daily earnings) associated with daily hours of work for citrus fruit pickers in California, though poor environmental conditions (ozone air pollution) did lead to a drop in earnings.[1] This does raise a potentially important distinction between mental and physical fatigue. Fruit picking is unlikely to be mentally challenging but is likely to be physically demanding, while other occupations may involve the opposite or indeed an interaction of the two. This interaction is important, as Marcora et al. (2009) show that mental fatigue can impair physical performance and limits short term endurance through perception of higher effort.

Turning to the sports economics literature, research on fatigue and performance is confined mainly to looking at the role of rest days between fixtures, rather than within game fatigue which would be more akin to the effect of extended hours in a more general labour market setting. Scoppa (2013) exploits variations in a team's rest days due to TV scheduling in the FIFA World Cup and UEFA European Football Championships. In more recent tournaments (1990's and onwards), rest days were found to have no impact on team performance even when

[1] It is unclear however, whether this was due to fatigue or simply a reduction in worker effort.

controlling for team quality factors.[2] Entine and Small (2008) consider the role of rest days in explaining home court advantage in the National Basketball Association (NBA), where away teams may be required play on successive days, a possible contributing factor to the observed 61% home win rate in the NBA. The home team scored on average 3.24 points more than the away team, of which a small (0.31), though significant, portion could be attributed to the limited number of rest days. Moreover, visiting teams with back-to-back games were an estimated 1.77 points worse off than a fully rested visiting team. Other notable work examines the effect of travel distance on performance, namely Oberhofer et al. (2010) for the German Bundesliga and Nichols (2014) for the National Football League (NFL). In both cases, more travel is associated with declines in performance, while the latter also finds that direction of travel is important.

Work examining within game fatigue is mainly confined to the sports medicine literature. Rampinini et al. (2009), studying Italy's Serie A football league is a good example. They find players who covered more distance in the first half not only ran less (at various intensities) in the second half, but also saw a decline in the number of successful short passes. They concluded that match related fatigue influences both physical and technical output.

There is a well-established literature examining muscular fatigue of baseball pitchers. However, many of these studies suffer from small sample sizes and are limited to laboratory setups rather than observing data from the real world. Escamilla et al. (2007) observed that both pitch velocity and pitching mechanics (the position of the pitcher's torso) were significantly different between the first and last two innings pitched before a pitcher said they were unable to continue. In this setup, pitchers were throwing between 105 and 135 pitches and so results may only be applicable to starting pitchers. In a video analysis of MLB pitchers at Spring Training, Murray et al. (2001) found that pitch velocity decreased by 5mph, while leg rotation, knee angle and forces exerted on the shoulder were all significantly different between the first and last innings. Finally, Lyman et al. (2002) report that high pitch counts amongst youth baseball pitchers are associated with a higher self-reported incidence of elbow and shoulder pain. This was particularly evident for curveballs and sliders, types of pitches that place high loads on these joints.

[2] Scoppa proposes that the reason tournaments before 1990 were affected by rest days was because the athletic preparation by teams and players was significantly worse than it is in modern day football.

2.2 Task Switching

In addition to fatigue, other studies have investigated the role of task switching and multitasking, each distinct behaviour, on productivity. Multitasking involves doing different tasks at the same time, while task switching involves doing different tasks sequentially, and evidence from Buser and Peter (2012) shows that this distinction is important. In their experiment, they randomly allocate participants into three groups; one group multitasking, one task switching at a time determined by the experiment, and a final group task switching at their own convenience.[3] Results suggest that subjects who multitasked perform worse than those who task switched, while surprisingly, being able to pick when to switch tasks was associated with worse performance.

It is unclear however, how such experimental evidence translates into the real world because of the different nature of the tasks involved. Jobs involving multitasking or task switching are now synonymous with modern day work, and thus it should be of great interest to managers to understand how (or if) it affects productivity. From relatively low skilled occupations such as supermarket assistants to higher skilled jobs such as teachers and physicians, all roles will require workers to carry out different tasks. Sports too offers several examples of players having to do different tasks. In football (soccer) and rugby for example, players are constantly switching between attacking and defending whenever ball possession changes, while in cricket and baseball, players are required to both field and bat.

Theoretically, Aral et al. (2012) suggest that task switching has ambiguous effects on productivity. On the one hand, an effective ability to task switch could allow workers to smooth their output during lulls in workload, while skill complementarities across tasks should benefit productivity. On the other hand, carrying out multiple tasks could cause delays and force the prioritisation of more important tasks, while switching between tasks is also associated with mental congestions and increased errors (see for example Rubinstein et al. (2001) or Kiesel et al. (2010)).

Turning to the industry specific evidence, Coviello et al. (2015) use a sample of Italian judges specialising in labour disputes who receive randomly assigned cases. Naturally, some of these cases are more complex and so take longer to complete. Their results suggest that judges respond to an increase in future workloads by juggling more cases in the present. In particular,

[3] In their experiment, the tasks included a Sudoku puzzle and a word search game

a 1% exogenous increase in workload increases the duration of trials by between 3 and 6 days, and judges would need to increase their effort by between 1.1% and 1.4% to maintain the same length of trials. A similar result is reported by Aral et al. (2012) using data on project outputs at an IT firm. They find that task switching increased total output, but this came at a cost of each project taking longer to complete. Singh (2014) studied physicians processing time, throughput rate and output quality from a hospital emergency department, and presents mixed evidence on the benefits of task switching (which in this setting refers to treating and attending to patients with different ailments). He finds that up to a value of about four patients per hour, task switching helps to reduce the time taken to process patients and reduces idle time. However, beyond this point, task switching eventually leads to fewer detected diagnoses and increases the likelihood of patients re-visiting the hospital within 24 hours.

Why then is there a need to re-visit this topic, and what are the benefits of using sports, specifically baseball data to address it? First, a common issue in assessment of performance in non-sports settings is that it can prove difficult to compare performance across different workers and across different firms. Moreover, performance on any one task may encapsulate several dimensions e.g. quantity of output, quality of output, or some combination of the two. In baseball, however, performance metrics are easily comparable across workers (in our case, pitchers) and firms (in our case, teams). Even though a pitch has several dimensions of quality, each provides a very clean assessment of performance, meaning pitches can be objectively assessed. Furthermore, the inherent structure of a game of baseball consisting of innings and a batting order makes it easy to identify a player's different roles. As such, this clear structure makes it easier to identify changes to performance in response to task switching. Perhaps most importantly, is that we are considering a high stakes setting where decisions have real and sizeable effects on outcomes of matches.

3. Industry Context: Baseball & Major League Baseball (MLB)

Baseball is a team sport played between two opposing teams, with each team sequentially batting and fielding. The game proceeds when a pitcher (one of nine positions on the defensive, or fielding team), standing on the pitcher's mound, throws to the batter, standing on the home plate. The batter continues to be pitched at until one of three possible outcomes: following three strikes[4], getting on base (either via hitting the ball into play, a walk, hit by pitch, or catcher's interference) or hitting a home run. The aim of the batter is to score runs by advancing around

[4] See section 4.1 for a full definition of a strike

three bases and back to home plate, while the pitcher should aim to prevent the batter from reaching base or advancing.

An entire game consists of 9 innings, during which each team plays both offense and defence, and the team with the most runs at this point wins the game.[5] Each inning itself consists of two half innings; a top (first) and bottom (second) half. In the top half, the home team pitches and the away team bats, and vice versa for the bottom half. A half inning consists of three outs (three players from the batting team getting out).

Major League Baseball consists of 30 teams (29 from the United States and one Canadian team) who play 162 games over the course of the regular season, spanning from early April until late September. This represents an intense schedule for the teams and the players, with games taking place on a far more frequent basis than other major global sports leagues.[6] The thirty teams are split into the American League (AL), founded in 1901 and the National League (NL), founded in 1876. Since 1903, these leagues have cooperated to run a single season ending championship (the World Series), but only in 2000 did the leagues merge into a single organisation. Each league is further split into 3 divisions (East, Central and West). The winners of each division along with two wildcards from each league (teams with the best remaining Win-Loss records) go on to play in a 10-team postseason knock out tournament, culminating in the World Series, pitting the winner of the AL against the winner of the NL.

Of the 162 regular season games, the current scheduling rules are that teams play 142 games against teams from the same league. These intra-league games consist of 76 games against teams within the same division and 66 games against teams from other divisions but in the same league. The remaining 20 games are inter-league games, with teams playing 10 of these at home and 10 away from home.

The rules and regulations across the two leagues are virtually identical. There is one exception, however, crucial to our analysis in identifying performance changes due to task switching. The AL operates under the Designated Hitter (DH) rule, allowing teams in the AL to nominate a player, the DH, to replace on player in the batting order. This is the DH's only role, and they do not fill any position on defence. Pitchers are customarily poor hitters, and so it is usually

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[5] If the game is tied at the end of 9 innings, additional innings are played until one team is ahead at the end of a given inning.
[6] Of the other major global sporting leagues, teams in the National Football League play 16 games over a 4 month period between early September and late December, teams in the National Basketball League play 82 games over the 7 months from October to April, while European football (soccer) leagues run from August to May with teams playing in the region of 34-38 games.

them who are replaced by the DH in the batting order. The NL on the other hand, does not use this rule.[7] As such, in the NL we observe pitchers having to both pitch (their primary role) and bat to attempt to advance round bases. Whereas in the AL, pitchers only pitch; they do not bat. MLB is rare in this regard of having a such a major rule difference being applied to its teams.[8] Other baseball leagues, such as high school leagues and collegiate level baseball usually adopt some variation of the rule, so it is rare that pitchers are required to bat. The Central League, one of two leagues in Japan's Nippon Professional Baseball league is the other notable exception where pitchers are required to bat.

In MLB, the rule was originally adopted by the AL in 1973 as an experiment in the face of low offensive output. The rationale was that if pitchers were poor hitters and fans value offensive output, then this was bad news for team owners who may suffer from declining attendances. Thus, the removal of a poor hitter (the pitcher) from the batting line up would help boost attendances (Domazlicky and Kerr (1990)). The DH rule has often been a source of debate between baseball traditionalists and those who want the game to be modernised, providing a fruitful source of discussion in the media, especially when high-profile pitchers get injured batting or running bases (see for example Cassavell, 2016).

In order for the DH rule to create a valid counterfactual for whether we observe pitchers task switching or not, our approach requires that pitchers are (as good as) randomly affected by this rule i.e. randomly allocated to the two leagues. To put this another way, we require that teams are not selecting pitchers based on their batting ability, and only hiring based on pitching ability. Taken on face value, this may seem implausible. However, this is a perfectly reasonable assumption to make given what we observe happening in reality. It also appears unlikely that teams would hire a pitcher based on their ability to bat, a skill which pitchers rarely practice throughout their high school and college career. Instead, teams hire pitchers on their primary skillset, pitching.[9] Incidentally, average batting statistics show pitchers are somewhat worse hitters compared to other positions, as demonstrated by Table 1 below, though perhaps not as different as one may anticipate. We don't see this as much an issue however, because of the

[7] During interleague play (i.e. an AL vs NL team), the rule is operational if the game is played at an AL ballpark.

[8] During the 2020 season, the NL approved use of the DH for first time as the MLB season was affected by the Covid-19 pandemic. The season was restricted to 60 games between July and October, and in an effort to prevent excessive fatigue during this period, the NL allowed a DH to replace the pitcher in the batting order. Our study period ends at the 2019 season however, and our results are not affected by this change. It also appears likely that the NL will adopt the DH rule as part of the new Collective Bargaining Agreement which will come into force ahead of the 2022 season, and thus the rules across the two leagues will be harmonised.

[9] Our results are robust to dropping the best pitchers in terms of their batting statistics from the sample.

argument outlined above; namely that pitchers are specialists and are hired to pitch. There are, of course, some rare exceptions to this assumption. Pitchers tend to move across to the NL later in their careers (when their ability is declining), while those pitchers who are good hitters are more valuable to NL teams. This could play a role in AL to NL trade negotiations.

Table 1: Batting Statistics by Position (2017-19)

Statistic	Non-Pitcher	Pitcher
Batting Average	0.256 (0.032)	0.247 (0.036)
Expected Batting Average	0.253 (0.027)	0.246 (0.031)
Slugging	0.433 (0.073)	0.411 (0.072)
Expected Slugging	0.428 (0.071)	0.410 (0.064)
Weighted On-Base Average	0.324 (0.039)	0.312 (0.039)
Expected Weighted On-Base Average	0.328 (0.037)	0.317 (0.035)

Standard Deviations in parentheses
Batting Average is determined by dividing a players hits by their total at-bats
Slugging (percentage) is calculated as the number of total bases divided by the number of at-bats
Weighted On-Base Average is a version of On-Base percentage accounting for how a player reached base, weighted by the relative values of each event
Expected Outcomes attempt to remove defence quality and ballpark effects
Statistics are for players with at least 200 plate appearances per season
Individual player statistics were sourced from Baseball Savant (www.baseballsavant.mlb.com)

4. Data

We examine pitch-by-pitch data for regular season MLB games for the seasons 2017, 2018 and 2019, sourced from Baseball Savant (www.baseballsavant.mlb.com). Our analysis begins in 2017 to avoid conflating changes in pitcher performance with changes in pitch measurement. Before 2017, different technology was used to record the pitch characteristics. Our analysis period ends at the 2019 season, because of the Covid-19 affected 2020 season where the season length was shortened to 60 games and teams were subjected to many temporary rule changes, including the temporary adoption of a universal DH rule. The data are nevertheless very large, with 7290 games and approximately 2.1 million individual pitches. The data include various characteristics of each pitch, most importantly to our work, velocity and location, as well as information about the outcome of each play (e.g. score, players on base). This information is captured by Trackman, a high accuracy tracking system introduced to all ballparks in 2015, replacing the camera based PITCHf/x system. Using these data, we are able to construct various outcomes of pitcher performance and define measures of both in game fatigue and task switching.

We limit our analysis to starting pitchers, a limitation that reduces our sample to about 1.3 million individual pitches. Primarily, we limit our analysis to starting pitchers because relief and closing pitchers rarely get a chance to bat or get on base, so there are few observed counterfactual opportunities. Moreover, only starting pitchers are likely to reach high enough pitch counts to be affected by severe fatigue.

4.1 Pitcher Performance

Baseball is well known for producing a multitude of statistics for evaluating player performance. Key to this study, however, is choosing outcomes that are independent (as much as possible) of the batter or luck in batting outcomes, but reflective of underlying pitching performance. One obvious choice is pitch velocity, because fatigued pitchers will not be able to throw as hard as a fully fit pitcher (Suchomel et al. (2014)). Velocity is also the outcome of choice in many sports science studies on pitcher fatigue (particularly those studying injury risk amongst pitchers e.g. Bushnell et al. (2010) and Keller et al. (2016)).

Our preferred specifications rely on samples restricted to fastballs to limit the effect to which strategy affects the results. Pitchers may purposely throw a slower pitch, such as a changeup or a curveball, after a sequence of fastballs with the aim of deceiving the batter, provoking them to swing too early and induce a bad contact. This drop in velocity is not necessarily indicative of a drop in performance. Over half of the 1.3 million pitches are categorised as a fastball, leaving us with just under 760,000 observations in the fastball sample. Figure 1 charts how likely pitchers are to throw a fastball as the game progresses. While the first pitch is almost certain to be a fastball, very quickly the probability drops to around 55-60%. Given this relative stability, our results should not be driven by pitch selection. The type of pitch is classified with the algorithm used by Statcast.[10]

We also use the location of the pitch as a measurable outcome of pitching performance, as there is a requirement to throw to certain locations in order to be successful: the strike zone. The strike zone, as defined by the Major League Baseball Rulebook is *"that area over home plate the upper limit of which is a horizontal line at the midpoint between the top of the shoulders and the top of the uniform pants, and the lower level is a line at the hollow beneath the kneecap"*. Figure 2 is the accompanying diagram (Official Baseball Rules, 2018

[10] Specifically, Four-Seam Fastballs (code FF), Two-Seam Fastballs (FT), Sinker (SI) and Cutters (FC) are classed as fastballs.

Figure 1: Probability of throwing a fastball

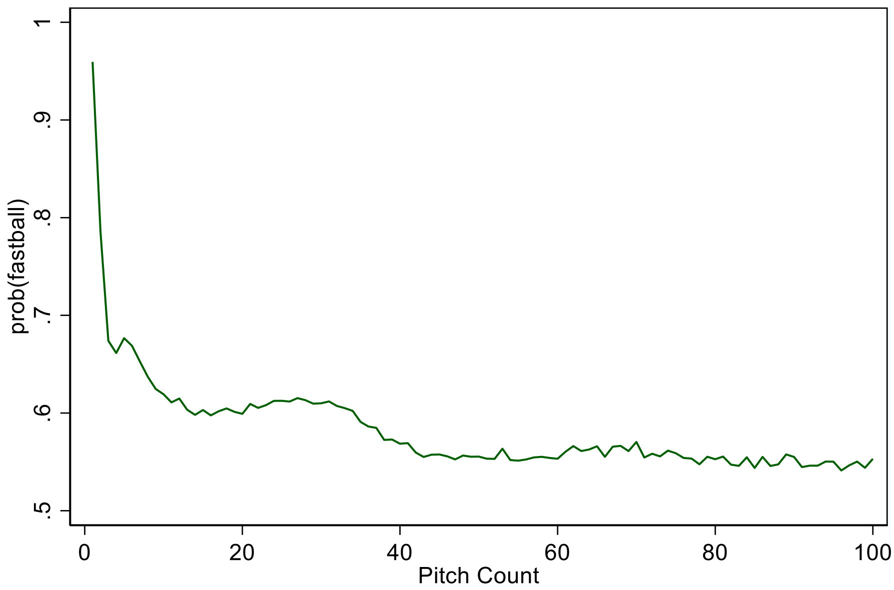
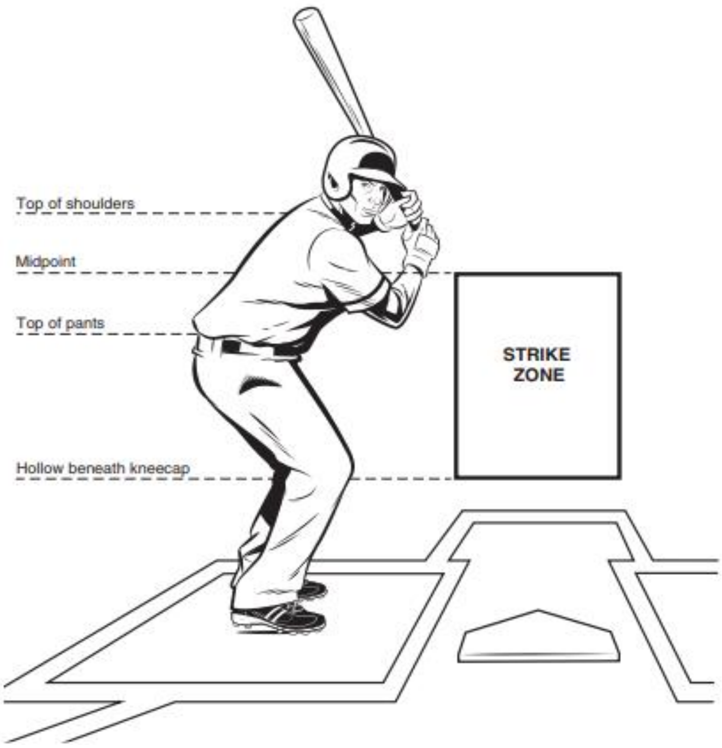


Figure 2: Definition of the Strike Zone



We define Pitch Location as the straight-line distance from the centre strike zone, calculated using the horizontal and vertical coordinates of the ball as it crosses home plate. A good pitch is considered to go through the edges of the strike zone, though not all pitches are intended to be thrown fully within this strike zone. Since our location definition could include both strikes and balls (a pitch thrown outside of the strike zone) depending on exactly how far from the centre the pitch is, we also use two binary variables to accompany this definition. The first of which, Strike, is equal to one if the pitch thrown is a strike. The second, Edge, is equal to one if the location of the pitch is within 1.5 inches either side of the edges of the strike zone. It may be advantageous for pitchers to throw pitches outside the strike zone with the intention of inducing weak contact by the batter, as pitches near the centre of the strike zone are more easily put into play by the batter. With the diameter of a baseball being 3 inches (so a radius of 1.5 inches) and Trackman measuring the location of the ball from its centre, any point of the baseball that just touches the edge of the strike zone will still be a strike. Whether this is called a strike by the umpire is a different story (see for example Mills (2014)) but having a pitcher who can throw that accurately is a sign of good performance.

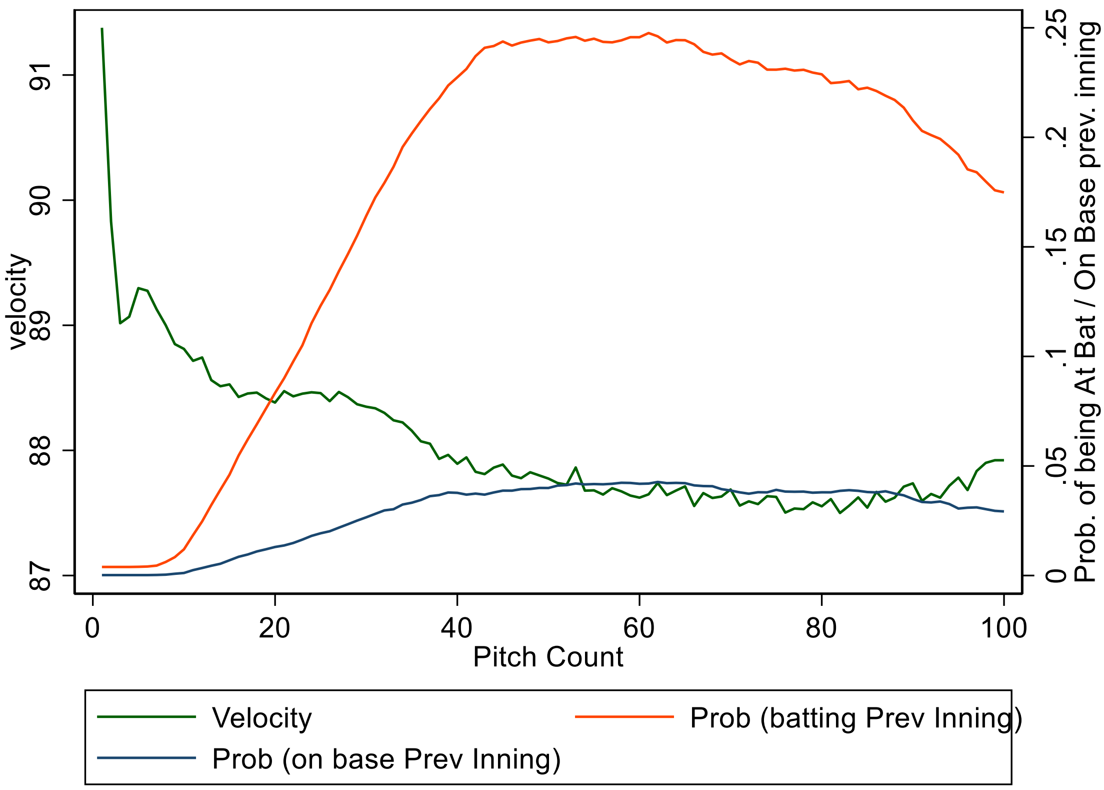
We also analyse several more objective measures of performance. Namely, whether a pitcher gives up a Walk (four pitches outside the strike zone not swung at by the batter, and the batter is awarded a first base), considered a very bad pitching outcome, whether the pitcher strikes out the batter (throws three strikes), considered a good pitching outcome, and the number of runs given up (opposition score).

4.2 Fatigue & Task Switching

To model the work done by a pitcher, we use a simple cumulative pitch count and its squared value. Our definition of task switching comes from pitchers having to bat and/or get on base during a game. In the most basic form, we define task switching using two binary variables (Pitcher Prev On Base and Pitcher Prev At Bat) identifying pitchers who have previously been at bat or on base at any point in the game up to their current pitch.

However, a drawback of this definition is that we may confuse the effects of task switching with a more general end of game fatigue effect. As an example, consider a pitcher pitching in the bottom of the 6th inning may. They might not have batted since the 3rd inning, but this would be treated as equivalent as a pitcher who batted more recently in the top of the 6th inning. It is unlikely that pitching in the 6th inning would be affected by batting in the 3rd, but it is conceivable that batting in the immediate past could have a more serious effect. As such, our preferred definition of task switching considers only task switching (previously at bat or previously on base) that occurred in the previous (half) inning.[11] This narrower definition should identify the immediate effects of task switching, if they exist, rather than potentially picking up a more general fatiguing effect due to extended play. Figure 3 graphs the how probability of batting in the previous inning (orange line, RHS scale) and the probability of getting on base (blue line, RHS scale) varies as a game progresses, along with the average velocity (green line, LHS scale). Whether we can discern any causal association between these variables is the question of the analysis that follows.

Figure 3: Average Velocity and Probability of Batting and Getting on Base



Of course, an at bat can result in several different outcomes, and what happens whilst at bat is a likely determinant of the subsequent pitching performance, rather than just batting per se. Certain outcomes are likely to involve a great deal more physical effort, such as sprinting to first base, while other outcomes may be less strenuous. As such, in Section 6.3 we offer an

[11] Defining task switching with **half** innings is key here. A pitcher pitching in the bottom of the (e.g.) 6th inning may have task switched in the top of the 6th, but a pitcher pitching in top of the 6th would have task switched in the bottom of the 5th inning.

analysis breaking down the result of the at bat into more granular events, focusing on singles, strikeouts, walks and field outs, to examine differential effects by batting outcome.

4.3 Descriptive Statistics

Table 2 below shows the descriptive statistics. Panel A is for all pitches thrown by starting pitchers, while Panel B is restricted to fastballs. The average point at which the starting pitcher is replaced is around pitch 89, with a maximum value of 134. Please see Appendix Table A1 for a breakdown of these statistics by league.

Table 2: Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max
Panel A: All Pitches (N=1,291,074)				
Pitch Count	46.72	27.93	1	134
Velocity (mph)*	88.11	5.88	40.90	101.90
Location - distance from centre of SZ**	1.14	0.63	0.00	11.32
Strike	0.46	0.50	0	1
Edge	0.18	0.38	0	1
Walk	0.02	0.14	0	1
Strikeout	0.06	0.23	0	1
Opposition Score	1.12	1.44	0	11
Prev At Bat	0.32	0.47	0	1
Prev At Bat (prev inning)	0.17	0.38	0	1
Prev On Base	0.07	0.26	0	1
Prev On Base (prev inning)	0.03	0.17	0	1
Balls	0.88	0.97	0	4
Strikes	0.89	0.82	0	2
Panel B: Fastballs (N=757,605)				
Pitch Count	44.94	28.25	1	134
Velocity (mph)$^{+}$	91.99	2.92	57.30	101.90
Location - distance from centre of SZ^{++}	1.06	0.55	0.00	9.69
Strike	0.47	0.50	0	1
Edge	0.19	0.39	0	1
Walk	0.02	0.15	0	1
Strikeout	0.04	0.20	0	1
Opposition Score	1.06	1.42	0	11
Prev At Bat	0.31	0.46	0	1
Prev At Bat (prev inning)	0.17	0.37	0	1
Prev On Base	0.07	0.26	0	1
Prev On Base (prev inning)	0.03	0.16	0	1
Balls	0.92	1.01	0	4
Strikes	0.82	0.82	0	2

Note: number of observations for velocity and location differ
* 1,285,793 ** 1,285,620 $^{+}$ 757,433 $^{++}$ 757,390

5. Estimation

Our model of pitch quality is as follows:

$$
\begin{aligned}
PitchQuality_{igt} \\
&= \beta_0 + \beta_1 Pitch\ Count_{igt} + \beta_2 Pitch\ Count_{igt}^2 + \beta_3 PrevAtBat_{igt} \\
&+ \beta_4 PrevAtBat * Pitch\ Count_{igt} + \beta_5 PrevOnBase_{igt} + \beta_6 PrevOnBase \\
&* Pitch\ Count_{igt} + \beta\boldsymbol{X} + PictherFE + BatterFE + MonthFE \\
&+ BallparkFE + YearFE + \epsilon_{igt}
\end{aligned}
$$

such that we compare performance pre- and post-switching tasks, with pitchers in the AL, or strictly speaking, pitchers playing at AL ballparks, acting as the control group. The subscripts refer to pitcher *i,* in game g, playing for team *t.* The outcome Pitch Quality is one of several measures discussed previously, namely, Pitch Velocity, Pitch Location, Strike (0,1), Edge Pitch (0,1), Walk (0,1), Strikeout (0,1) and Opposition Runs given up. Velocity is measured at the point of release. It is possible to measure velocity at various points along the trajectory of a pitch, but these could be affected by other variables such as wind conditions, air pressure, spin etc. and as such velocity at the point of release would be the most comparable across pitches.

Prev At Bat and Prev On Base are the task switching variables and can be defined either for any point over the game up the current pitch or, our preferred definition, restricted to just the previous (half) inning. Month Fixed Effects are potentially important in explaining temperature variations across the season, where in hotter months pitchers may fatigue quicker, and could also explain a general decline in performance over the course of a season. We also control for the possible differing effects by ballparks, with different altitudes, air pressures, wind conditions etc. all possibly playing a role in the observed pitching outcomes.

Within the vector **X**, we include the number of balls and strikes that the pitcher has thrown during the current plate appearance (known as the count). These are important factors to consider since different counts are associated with favourable outcomes for either the batter or the pitcher, and thus may be associated with different levels of mental pressure. When a pitcher is faced with allowing a walk, pitchers are more likely to throw strikes down the centre, particularly fastballs. Though, when pitchers are in charge of the at bat (e.g. 0-2 count), they can be slightly riskier and aim for the extremities of the strike zone, attempting to get the batter to swing and strike out. For opposition runs, we also include indicators of whether a runner is currently standing on 1^{st}, 2^{nd} or 3^{rd} base.

There are two possible issues that threaten our estimation. One is that our assumption of teams in both leagues only hiring pitchers based only on their pitching ability not holding. The second is of within game selection of pitchers i.e. when the manager decides to pull the starting pitcher and replace them with a relief pitcher; a point in the game when the starter is considered too fatigued to be effective. Work by Finigan et al. (2020) shows that this decision is, on average, made at an efficient point in the game by managers. Nevertheless, some pitchers will still last longer than other, and so it is likely that pitches we observe later in games, or in later innings, belong to pitchers who are better at dealing with the effects of fatigue, and/or simply having a good game.

We address both these possibilities in our Robustness Checks in Section 6.5. To deal with the former, we exclude pitchers with the best batting statistics, which acts as a proxy for their batting ability. For the latter, we offer regressions including the lagged average inning velocity as a predictor. The starting pitcher will be pulled at some point in the game, usually when fatigue sets in and prevents them from pitching as well. By including lagged inning velocity, we can control for pitchers finishing an inning strongly and being more likely to allowed to carry on into the next inning. We also restrict the timeframe of innings over which we consider our estimations. This allows us to consider ranges of the game both where starting pitchers should not yet have been pulled, and also have a reasonable high probability of having task switched (in line with Figure 3).

6. Results

6.1 Velocity

We first present results from the velocity regressions in Table 3. It is clear that higher pitch counts are associated with declining velocity, albeit at a declining rate. Each pitch loses around 0.05-0.06 mph in velocity. To put this another way, after about 16-20 pitches, velocity has dropped by 1 mph. The squared term indicates a turning point of around 76 pitches, varying slightly by specification. This is slightly lower value than the pitch count at which starting pitchers tend to be pulled on average, which is approximately 89. For fastballs however, each additional pitch does not see the same decline in velocity (between 0.019 and 0.01 drop in velocity per fastball pitched). Though again, this occurs at a declining rate, given the positive squared term. The decline in velocity is likely capturing the gradual decline due to fatigue as the game progresses.

Moving from left to right in Table 3 we move towards our preferred specifications; in columns 4-6 using previously at bat / on base in the previous inning, and then in the final three columns restricting the sample to fastballs, where we can rule out any strategic effects. Even with the inclusion of pitcher and batter fixed effects in column 8 and then month, ballpark and year fixed effects in column 9, we observe that batting in the previous inning contributes positively to velocity, adding roughly 0.1 mph to the release speed of fastballs. Each additional pitch thrown after this gradually reduces in velocity. However, the magnitude of the interaction with pitch count is, in many specifications, extremely small compared to the uninteracted Prev At Bat, and thus the effect would seem to be long lived. In our preferred specifications 8 and 9 for example, the models suggest that between 80 and 90 pitches are required for the initial positive effect to be wiped out. Given that in these models we measure task switching across innings (which on average last around 16 pitches, std.dev=6), and that pitchers on average last around 89 pitches (std.dev=18), this interaction effect pales into sporting insignificance. There is no significant additional effect from being on base in all but one of the specifications.

Table 3: Velocity	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES				All Pitches				Fastballs	
Pitch Count	-0.053***	-0.048***	-0.048***	-0.050***	-0.049***	-0.048***	-0.016***	-0.009***	-0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Pitch Count Squared	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Prev On Base	-0.022	0.044	0.043						
	(0.069)	(0.063)	(0.063)						
Pitch Count * Prev On Base	-0.000	-0.001	-0.001						
	(0.001)	(0.001)	(0.001)						
Prev At Bat	0.443***	0.049	0.068**						
	(0.036)	(0.033)	(0.034)						
Pitch Count * Prev At Bat	-0.003***	-0.002***	-0.002***						
	(0.001)	(0.001)	(0.001)						
Prev On Base (prev inning)				-0.234**	-0.061	-0.073	0.008	0.023	0.013
				(0.096)	(0.088)	(0.088)	(0.061)	(0.037)	(0.037)
Pitch Count * Prev On Base (prev inning)				0.003**	0.001	0.001	-0.000	-0.000	-0.000
				(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Prev At Bat (prev inning)				0.306***	0.053	0.069*	0.119***	0.091***	0.105***
				(0.041)	(0.038)	(0.038)	(0.026)	(0.016)	(0.016)
Pitch Count * Prev At Bat (prev inning)				-0.001**	-0.000	-0.000	-0.001*	-0.001***	-0.001***
				(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Balls	0.653***	0.673***	0.673***	0.652***	0.673***	0.673***	0.021***	0.011***	0.011***
	(0.006)	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.004)	(0.002)	(0.002)
Strikes	-0.449***	-0.475***	-0.474***	-0.450***	-0.474***	-0.474***	0.404***	0.404***	0.404***
	(0.007)	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)	(0.004)	(0.003)	(0.003)
Times through order	-0.450***	-0.232***	-0.240***	-0.438***	-0.230***	-0.237***	-0.158***	-0.040***	-0.045***
	(0.014)	(0.015)	(0.015)	(0.014)	(0.015)	(0.015)	(0.009)	(0.007)	(0.007)
Constant	89.758***	89.551***	89.555***	89.732***	89.556***	89.558***	92.191***	92.002***	92.003***
	(0.019)	(0.018)	(0.018)	(0.019)	(0.018)	(0.018)	(0.012)	(0.007)	(0.007)
Observations	1,285,793	1,285,788	1,285,788	1,285,793	1,285,788	1,285,788	757,433	757,414	757,414
Pitcher & Batter FE	NO	YES	YES	NO	YES	YES	NO	YES	YES
Month, Ballpark & Year FE	NO	NO	YES	NO	NO	YES	NO	NO	YES
R-squared	0.021	0.195	0.196	0.020	0.195	0.196	0.017	0.647	0.651

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

6.2 Other Outcomes

Next, we focus on our other indicators of pitching performance. Table 4 below displays the regression results for our three indicators of pitch location, namely Distance from the Centre of the Strike Zone (labelled Location), and our two binary variables Strikes and Edge Pitches. We analyse the latter two outcomes using a Linear Probability Model because of the desire to include the various Fixed Effects in the models, which surpasses the need for a Probit / Logit regression. Pitch location is possibly a very noisy indicator of pitcher performance, since such small differences in location can determine success or failure, but still has value in that pitches around the edge or corners of the strike zone are considered harder to hit.[12]

The effect of a higher pitch count is that pitch location gets further away from the centre of the strike zone. This result has two possible interpretations. Either that these pitches further away from the centre of the strike zone are better pitches, in that they are still within the confines of the strike zone but getting closer to the edges, or that they are now worse pitches, since they now lie outside the strike zone. This is where the analysis of Strikes and Edge Pitches is useful, and columns 3-6 in Table 4 show the latter case to be true. Higher pitch counts reduce the probability of throwing both strikes and edge pitches, indicating a lack of command or control as the game progresses.

On the effects of task switching, there appears to be very little in the way of any effect, positive or negative, from batting and running bases. The strongest predictors of locational outcomes are the number of balls and strikes (the count). A higher ball count is associated with pitches getting closer to the centre. These would be regarded as safer pitches since the pitcher does not want to give up a walk. While a higher strike count means the pitcher can afford to throw riskier pitches, with the aim of hitting the extremities of the strike zone making it harder for batters to know whether to swing and risk bad contact, or not swing and risk an out.

We next turn our attention to Table 5, where we consider Walks, Strikeouts and Opposition Score.[13] Walks occur when a pitcher throws four pitches called as balls by the umpire (i.e. outside the strike zone and not swung at by the batter), and in turn the batter is awarded a first base. These are considered a bad outcome for pitchers and is something they should look to

[12] The fastball specifications are potentially important for explaining locational outcomes too, since the types of pitches thrown over the course of a game could change resulting in pitches getting closer to the center.
[13] In Table 5, we drop the number of pre-play balls in the count from the walk model, since a walk is awarded after 4 balls, so the pitcher must be on 3 balls for a walk to occur. Equally, we drop the number of strikes from the strikeout model since there must already be 2 strikes in the count for a strikeout to be possible.

avoid. Pitchers appear marginally less likely to give up walks after batting, which could offset the increased likelihood of giving up walks as the game progresses. This result, however, is only significant at the 10% level, and drops out of significance when using the fastball sample. Interestingly, we observe that pitchers are less likely to strikeout after batting in the previous inning. This would be considered a bad outcome for pitchers. While it is possible that this somewhat contradictory finding is simply a product of noise, we believe there is a valid explanation behind it in the context of task switching. If the act of batting keeps the pitcher active between innings (for example, preventing them from stiffening up between innings), then physical output / performance may improve (i.e. higher velocity). If the task switching is a mental task however, then this may have implications for the pitcher's decision making. The net result could be less successful outcomes, despite improved physical performance. Moreover, effort does not necessarily have to translate into improved performance. Velocity (and location to a lesser extent) is (are) directly controllable by the pitcher, but whether the pitcher strikes out the batter is also dependent on the effort and performance of the batter.

Finally, we focus on runs given up in columns 5 and 6 of Table 5. In the mind of the pitcher, their most likely objective function is to try and minimise opposition runs. The outcome variable here is the score of the opposition (batting) team measured after each pitch (rather than before a pitch). Countering the increased runs given up as the game progresses is the negative effect of batting in the previous inning. Results suggest that pitchers give up between 0.23 and 0.25 fewer runs when pitching in the inning immediately after their at bat. However, working in the opposite direction is the positive effect of previously getting on base i.e. giving up more runs after getting on base. These two effects cancel each other out to some extent, thus we test the relative size of these two coefficients in each regression. We test the null hypothesis that the sum of these coefficients is equal to zero, with results being displayed in the row labelled Test (p val). We can reject this null hypothesis at conventional levels of significance. So, pitchers who only bat and fail to get on base give up fewer runs, while the overall effect for those pitchers who do get on base, is on average, still that they give up fewer runs, just not to the same extent had they have not got on base. The implication here is that pitchers should keep active between the innings pitched i.e. bat, but to not get too fatigued by running the bases. Getting on base would appear to fatigue a pitcher and their pitching performance suffers as a result. But simply being active and not sat on the side-lines in between innings is beneficial to their subsequent pitching performance.

Table 4: Locational Outcomes	(1)	(2)	(3)	(4)	(5)	(6)
	Location		Strike (0,1)		Edge (0,1)	
VARIABLES	All Pitches	Fastballs	All Pitches	Fastballs	All Pitches	Fastballs
Pitch Count	0.000*	0.000**	-0.000***	-0.001***	-0.000***	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Pitch Count Squared	-0.000***	-0.000***	0.000***	0.000***	0.000***	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Prev On Base (prev inning)	-0.001	0.019	-0.003	-0.012	-0.006	-0.013
	(0.010)	(0.012)	(0.008)	(0.011)	(0.006)	(0.008)
Pitch Count * Prev On Base (prev inning)	-0.000	-0.000**	0.000	0.000**	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Prev At Bat (prev inning)	-0.006	-0.003	-0.001	0.001	0.003	0.005
	(0.004)	(0.005)	(0.004)	(0.005)	(0.003)	(0.004)
Pitch Count * Prev At Bat (prev inning)	0.000	0.000	0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Balls	-0.107***	-0.085***	0.034***	0.029***	0.010***	0.007***
	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)
Strikes	0.158***	0.109***	-0.063***	-0.060***	-0.017***	-0.010***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Times through order	0.021***	0.017***	-0.014***	-0.015***	-0.001	-0.001
	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)
Constant	1.062***	1.019***	0.513***	0.522***	0.189***	0.197***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)
Observations	1,285,615	757,371	1,291,069	757,586	1,291,069	757,586
Pitcher & Batter FE	YES	YES	YES	YES	YES	YES
Month, Ballpark & Year FE	YES	YES	YES	YES	YES	YES
R-squared	0.055	0.045	0.019	0.021	0.003	0.004

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Walks, Strikeouts and Opposition Score	(1)	(2)	(3)	(4)	(5)	(6)
	Walk (0,1)		Strikeout (0,1)		Opposition Score	
VARIABLES	All Pitches	Fastballs	All Pitches	Fastballs	All Pitches	Fastballs
Pitch Count	0.000***	0.001***	0.001***	0.001***	0.025***	0.025***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Pitch Count Squared	-0.000***	-0.000***	0.000***	0.000	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Prev On Base (prev inning)	0.000	0.002	0.000	0.001	0.185***	0.157***
	(0.002)	(0.003)	(0.004)	(0.004)	(0.020)	(0.026)
Pitch Count * Prev On Base (prev inning)	-0.000	-0.000	-0.000	0.000	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Prev At Bat (prev inning)	-0.002*	-0.002	-0.006***	-0.006***	-0.276***	-0.282***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.009)	(0.011)
Pitch Count * Prev At Bat (prev inning)	0.000	0.000	0.000***	0.000***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
On 1st					-0.077***	-0.075***
					(0.002)	(0.003)
On 2nd					0.048***	0.051***
					(0.003)	(0.004)
On 3rd					0.131***	0.137***
					(0.004)	(0.005)
Times through order	-0.010***	-0.012***	-0.023***	-0.020***	0.517***	0.510***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.003)	(0.005)
Balls			0.031***	0.024***	-0.009***	-0.009***
			(0.000)	(0.000)	(0.001)	(0.001)
Strikes	0.014***	0.015***			-0.022***	-0.028***
	(0.000)	(0.000)			(0.001)	(0.002)
Constant	0.009***	0.013***	0.042***	0.032***	-0.506***	-0.496***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.004)	(0.005)
Test (p val)					0.000	0.000
Observations	1,291,069	757,586	1,291,069	757,586	1,291,069	757,586
Pitcher & Batter FE	YES	YES	YES	YES	YES	YES
Month, Ballpark & Year FE	YES	YES	YES	YES	YES	YES
R-squared	0.012	0.014	0.030	0.027	0.273	0.283

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

6.3 Singles, Walks, Strikeouts and Field Outs

From the previous section, we have uncovered a generally, though not uniform, positive effect on pitching performance for pitchers who have previously been at bat. We have also observed an additional effect of getting on base working in the opposite direction, albeit not always significant. To this point, the definition of an At Bat and On Base has considered them to be binary events. However, batting and getting on base are more than just binary events. For example, whilst batting a batter may swing and miss at three strikes and get an out, they could be awarded a walk to first base without swinging at all, they could hit a pitch into play and sprint to first base and so on. All these events are likely to induce different physical and mental responses. As such, we continue by exploring the importance of what happens at bat, and if the pitcher does make it to base, whether it matters the way that happens (walk, hit etc.). Specifically, we focus on four batting outcomes: Singles and Walks (resulting in the batter getting to first base, but a Single likely involving more effort), and Strikeouts and Field Outs (resulting in the batter getting an out).[14]

From Table 6, it appears to matter, first if, and second how pitchers got to base. Getting a single, a fairly strenuous activity involving sprinting 90 yards from home plate to first base, is associated with a drop in velocity, though only significant at the 10% level. Perhaps more notable, getting a single is associated with giving up more runs in the following half inning when pitching, which follows from the positive Prev On Base coefficients in columns 5 and 6 of Table 5. If the pitcher gets on base via a walk, then there is less of an impact on their subsequent pitching performance. This is perhaps not surprising given that a walk is less strenuous than getting a single. However, in cases where the pitcher does not get to base (strikeouts and field outs), velocity improves, certainly for the latter, which follows from results in Table 3, while on average 0.2 and 0.25 fewer runs are given up in the following half inning after these events, which follows from the negative Prev At Bat coefficients from columns 5 and 6 of Table 5.

[14] Statcast lists a total of 32 different outcomes following a plate appearance, however, some are so rare that we would gain very little by examining them. These four outcomes (singles, strikeouts, walks and field outs) are four outcomes that are a combination of the most common and interesting events to examine.

Table 6: Splitting the result of an At Bat PREVIOUS BATTING EVENT		(1) Velocity	(2) Location	(3) Strike (0,1)	(4) Edge (0,1)	(5) Walk (0,1)	(6) Strikeout (0,1)	(7) Opposition Score
Single	All Pitches	-0.196*	0.006	0.003	-0.009	-0.002	-0.007	0.090***
		(0.113)	(0.013)	(0.010)	(0.008)	(0.003)	(0.005)	(0.026)
	Fastballs	-0.024	0.020	-0.010	-0.011	-0.000	-0.007	0.089***
		(0.048)	(0.015)	(0.014)	(0.011)	(0.004)	(0.006)	(0.033)
Walk	All Pitches	0.145	-0.019	-0.013	0.001	-0.006	-0.013	0.077*
		(0.190)	(0.022)	(0.018)	(0.014)	(0.005)	(0.008)	(0.044)
	Fastballs	0.189**	0.021	-0.025	-0.003	-0.003	-0.010	-0.014
		(0.080)	(0.025)	(0.023)	(0.018)	(0.007)	(0.009)	(0.055)
Strikeout	All Pitches	0.015	-0.013**	0.003	0.004	-0.005***	-0.009***	-0.207***
		(0.052)	(0.006)	(0.005)	(0.004)	(0.001)	(0.002)	(0.012)
	Fastballs	0.057***	-0.013*	0.011*	0.005	-0.005**	-0.005**	-0.219***
		(0.022)	(0.007)	(0.006)	(0.005)	(0.002)	(0.003)	(0.015)
Field Out	All Pitches	0.124**	-0.000	-0.001	0.002	-0.002	-0.009***	-0.253***
		(0.060)	(0.007)	(0.006)	(0.004)	(0.002)	(0.003)	(0.014)
	Fastballs	0.083***	0.010	-0.004	0.006	-0.002	-0.010***	-0.253***
		(0.025)	(0.008)	(0.007)	(0.006)	(0.002)	(0.003)	(0.017)

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Each coefficient is a result of a separate regression. All regressions include Pitcher, Batter, Month, Ballpark and Year FE

6.4 Interleague Play

As a final demonstration of the benefits of task switching, we offer an analysis of the performance of pitchers during interleague (IL) games. To do so, we first restrict analysis to pitchers pitching away from home to remove any familiarity effects associated with playing at home i.e., home advantage. By doing so we compare performance of away pitchers in intra-league games (AL@AL or NL@NL) to their performance in inter-league games (AL@NL or NL@AL).[15] The analysis has two aspects to it since the use of the DH rule is determined by the identity of the home team. Thus, IL games played in AL (NL@AL) ballparks will use the DH rule, and NL pitchers who are used to having to task switch will now only be required to pitch since their position in the batting order can now be filled by the DH. In IL games played at NL ballparks (AL@NL) however, the DH rule will not be active, so AL pitchers who are used to only pitching are now required to bat as well. We can now analyse the effects of dropping a familiar task and also of adopting an unfamiliar task. Results are shown in Table 7 below.

[15] The use of the @ symbol is how matchups are denoted in MLB. It is quite literally saying the away team playing 'at' the venue of the home team.

Table 7: Interleague Play	FE	Fastballs	Outcome	Prev At Bat (prev inning)	Prev On Base (prev inning)	Observations
Panel A	Pitcher, Batter	No	Velocity	-0.201	0.560*	314,973
AL@NL	+Month, Ballpark, Year	No		-0.127	0.442	314,973
Pitcher is adopting batting	Pitcher, Batter	Yes		0.007	0.017	182,232
in the IL games	+Month, Ballpark, Year	Yes		0.039	-0.094	182,232
	Pitcher, Batter	No	Opposition Score	-0.034	0.075	315,959
	+Month, Ballpark, Year	No		-0.023	0.030	315,959
	Pitcher, Batter	Yes		-0.071*	0.005	182,254
	+Month, Ballpark, Year	Yes		-0.064	-0.037	182,254
Panel B	Pitcher, Batter	No	Velocity	0.104*	-0.004	322,115
NL@AL	+Month, Ballpark, Year	No		0.108**	-0.014	322,115
Pitcher is giving up batting in the	Pitcher, Batter	Yes		0.045**	0.072	192,492
IL games	+Month, Ballpark, Year	Yes		0.046**	0.066	192,492
	Pitcher, Batter	No	Opposition Score	-0.200***	0.175***	323,749
	+Month, Ballpark, Year	No		-0.197***	0.172***	323,749
	Pitcher, Batter	Yes		-0.205***	0.140***	192,602
	+Month, Ballpark, Year	Yes		-0.204***	0.138***	192,602

The results raise an interesting asymmetry, in that it appears to matter if pitchers are accustomed to switching between pitching and batting or not. Generally, AL pitchers playing in IL games at NL ballparks (Panel A) do not suffer any significant adverse effects, either in terms of reduced velocity or runs given up following batting compared to playing away from home but in other AL ballparks where they are not required to bat. However, NL pitchers throw faster pitches and give up fewer runs after batting in away games within their own league, compared to the case where they are not required to bat in away games played in AL ballparks. In other words, batting appears to be beneficial, but only to those pitchers who are accustomed to taking on the additional demands associated with task switching.

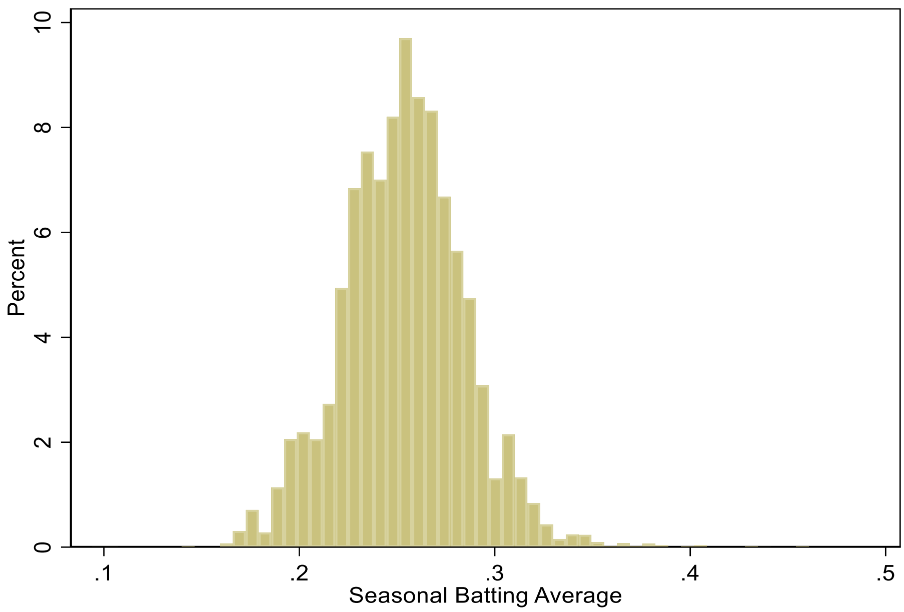
6.5 Robustness Checks

6.5.1 Selection of Pitchers to Leagues

To this point, our analysis has rested on the assumption that pitchers are not hired by teams based on their batting ability, and instead are hired only on their pitching ability. By making this assumption, we can say that pitchers are as good as randomly allocated to the two leagues, and in turn, randomly affected by the Designated Hitter forcing some to task switch. In the main, we believe this to be a perfectly reasonable assumption. Pitchers tend to be poor hitters and it is a skill that they rarely (if at all) train from high school all the way up to and including their professional careers. There are of course exceptions to this rule, albeit rare exceptions; some pitchers may be good hitters, and exceptional batting ability could play a role in AL to NL trade negotiations, where these pitchers will be of greater value to teams in the NL.

To test this assumption, we check the robustness of our results to excluding the best pitchers in terms of their batting statistics, with results shown in the Appendix Table A2. Specifically, we exclude any pitcher whose seasonal batting average was above 0.300.[16] This value was chosen as it is widely considered to a benchmark for very good batting. It has also been shown to be an important reference point that baseball players try to reach (Pope and Simonsohn (2011) and Tanji (2021)).[17] Figure 4 shows the histogram for pitcher's batting averages in each of the three seasons under consideration. Dropping players whose seasonal batting average is above 0.300 reduces the number of individual pitches under consideration by approximately 83,000, and cuts 117 pitchers from the sample, or 133 pitcher-season combinations. Regression results using this reduced sample are extremely similar to the results as shown in Table 3 (for Velocity) and Table 5 (for Opposition Score), meaning we can be confident that our results are unlikely to be driven by teams in the NL selecting pitchers based on their batting ability.

Figure 4: Histogram of Pitchers' Seasonal Batting Average



[16] Batting Average is calculated by dividing a player's total hits by his total at-bats, producing a statistic between 0.000 and 1.000 (reported to 3dp).
[17] Notice in Figure 4 the 'dip' at 0.300 and the bunching just above 0.300. This is precisely the reference point. Batters who are close to this point near the end of the season will try to finish with a BA of just greater than 0.300. The work by Tanji shows this is a reference point not motivated by monetary incentives.

6.5.2 Within Game Selection

The second threat to our identification comes from a selection bias arising from some pitchers being able to last longer in games. These pitchers may be of better ability, or just simply better able to deal with the effects of fatigue. The effect could be pitcher specific (across games) or pitcher-game specific (within game i.e. a pitcher is just having a good game). Either way, it could be that the positive effect we observe from batting in the previous inning is just a by-product of us observing these more robust pitchers lasting longer in games before replacement. This point is highlighted by the apparent upturn in velocity in Figure 3, where average pitch velocity increases slightly after around pitch 80. What we are likely observing here is observations coming from pitchers who are lasting longer in games before replacement because they are less fatigued.

We address this concern with two separate approaches. First, in Appendix Table A3 we present regressions similar to those in Table 3, but with the addition of the average velocity from the previous inning as a covariate. The logic of including this variable is that poor performance in the previous inning should be associated with being pulled. Alternatively, pitchers who finish the last inning strongly will be more likely to be allowed to continue. The effect of batting in the previous inning remains positive and highly significant even with the inclusion of the lagged average inning velocity.

Our second, preferred, check involves restricting the inning number(s) over which we consider our estimations. By removing later innings, we (roughly speaking) remove any pitchers who are having a very good game and lasting longer than usual, while by removing early innings, we exclude the early part of the game where there is a very low probability that pitchers have been given an opportunity to bat (see Figure 3). For reference, in the unrestricted sample, the last inning a starting pitcher appeared in was the 9^{th} inning, though usually, starting pitchers last until around the 6^{th} inning before being pulled. By running our models with the various inning restrictions in place (see Appendix Table A4), our results stay largely intact. This is especially true when we remove the first inning from consideration, a period of the game when pitchers are unlikely to appear at bat since they tend to be placed at the bottom of the batting order. Of note for our concerns over in game selection of pitchers, however, is that the removal of later innings does not dampen the effect of previously batting.

6.5.3 Placebo Check

As a final robustness check, we carry out a placebo style test, with results shown in Appendix Table A5. This test has 2 aims; first, and most importantly, to check that we do not find an effect of batting and / or getting on base when there should not be one. Second, we can rule out any anticipatory effects of pitchers who are up to bat in the forthcoming inning. To do this, we assign the at bat / on base to the inning before it happened. For example, a pitcher pitching in the bottom of the third inning having batted in the top of the third would ordinarily be assigned a value of 1 for the task switching variable Prev At Bat (prev. inning) when pitching in the bottom of the third. In the placebo check, we also (falsely) assign an at bat to the pitches thrown in the bottom of the second inning i.e. before they actually batted, and these are indicated with the addition of FALSE after the variable name. We repeat the procedure for getting on base as well.

Given these variables will be occurring earlier in games than the true at bat / on base, one may expect these coefficients to be positive, simply picking up the effects of a period of the game where pitchers are as fatigued. Thus, our placebo test involves comparing the coefficients of the FALSE and the true task switching variables. The row labelled "Test of equality (p value)" is testing the null hypothesis that Prev At Bat (prev inning) is equal to Prev At Bat FALSE. In our preferred fastball specifications, the null of equality of these coefficients is rejected. This gives us additional confidence in our results, in that we are finding a significant effect from task switching when we would expect to find one.

7. Discussion & Conclusion

Attempting to quantify the effects of task switching on short term (in our setting, that translates to within game) fatigue and productivity is not a straightforward task, not least due to difficulties in defining and comparing performance. Using play by play data from three seasons of MLB, we can overcome this difficulty and have shown task switching in the form of batting in the previous (half) inning results in largely beneficial effects on pitching performance.

In our preferred specifications, relying on fastballs and the inclusion of pitcher, batter, month, ballpark and year fixed effects, the average fastball velocity increased by up to 0.1 mph, and pitchers gave up 0.25 fewer runs in the half inning immediately following the at bat. At first this result may seem counterintuitive under the prior assumption that switching between batting and pitching may incur a switching cost and additional physical exertion whilst batting. However, we would not be the first empirical paper to find evidence that *some* task switching can be beneficial to performance. Namely, Singh (2014) found that up to about four patients per hour, physicians performance improved for each additional patient. Only after this point did the extra demands from task switching hinder performance. Moreover, if we are to assume that having to switch tasks within games creates a more challenging working environment, then according to Hommel et al. (2012), there is both behavioural and neuroscientific evidence that when faced with increasing difficulty of tasks, subjects increase their effort to compensate for and overcome that challenge. This phenomenon has also been shown experimentally by Srna et al. (2018). Our results are robust to accounting for pitcher ability, and to the consideration of within game selection of pitchers.

However, this improvement in performance after task switching was not uniform across all our outcomes. Pitchers were less likely to strike out the batter after batting, which we believe could highlight the importance of distinguishing between mental and physical effects due to task switching. Some outcomes also show a decline in performance after the pitcher gets on base, though the effect is not large enough to outweigh the initial positive effect of batting. So, on average, the overall effect from task switching remains positive. The practical implication for baseball teams and baseball managers is that they should be keen for their pitchers to go and bat, just to keep their minds active and not sit around on the side-lines, but at all costs should tell them to avoid them getting on base.

As for how we can explain these results in a baseball setting, it is possible that the switch between pitching and batting offers pitchers an opportunity to recuperate both mentally and physically. It could be for example, that batting acts as a distraction from the core task. A pitcher between innings but not batting would have more time to dwell on any previous mistakes which in their mind would eventually lead to replacement. Batting could simply reduce any mental stress associated with pitching. There could also be a physical reason; if pitchers begin to stiffen up whilst between innings, then batting may help loosen their joints and muscles in preparation for pitching. Running bases, however, may result in too much physical exertion overall, particularly if pitchers are left on base at the end of the half inning just before they are required to switch immediately back to pitching. Further work would be required to identify the channel of causality.

This does raise an interesting dilemma for MLB teams in the future. It appears increasingly likely that the NL will permanently adopt the DH rule following its temporary use for the Covid-19 affected 2020 season, especially with the current collective bargaining agreement (the agreement between players and the league) coming to an end in December 2021. On the one hand, pitcher performance may be harmed if the task switching element of a pitcher's game is taken away by the NL's adoption of the DH rule, since we have shown that task switching is beneficial to their performance. On the other hand, the removal of the requirement for pitchers to bat would remove a level of complication and strategy for coaches in the NL to consider. The 'Double Switch' is one such example of this.

As for how generalizable these results are to other sports and indeed other industries, there is certainly scope to abstract away from baseball. Cricket would provide an interesting sporting parallel. While other sports such as football (soccer) and rugby do involve players carrying out different roles (i.e. attacking and defending), the sequential nature of these tasks is not as well defined as in baseball. More generally, a scenario where temporarily moving away from one's main task would fit the same story. For example, an academic researching their work may attend seminars in a different area, then head off to give a lecture. Other occupations, particularly those involving manual or physical labour, may also be applicable to our results from the baseball setting.

APPENDIX

Table A1: Descriptive Statistics by League **Variable**	**National League** **Mean**	**American League** **Mean**	**Difference in means (p val)**
	N=650,229	N=640,845	
Pitch Count	46.587	46.847	0.000
Velocity (mph)*	88.229	87.987	0.000
Location - distance from centre of SZ**	1.137	1.147	0.000
Strike	0.462	0.456	0.000
Edge	0.179	0.179	0.430
Walk	0.020	0.020	0.294
Strikeout	0.056	0.054	0.000
Opposition Score	1.100	1.138	0.000
Prev At Bat	0.630	0.000	0.000
Prev At Bat (prev inning)	0.338	0.000	0.000
Prev On Base	0.145	0.000	0.000
Prev On Base (prev inning)	0.056	0.000	0.000
Balls	0.877	0.887	0.000
Strikes	0.891	0.890	0.366

Note: number of observations for Velocity and Location differ
* 647,102 (NL), 638,691 (AL)
** 647,011 (NL), 638,609 (AL)

Table A2: Removing Pitchers with BA>0.300	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Velocity				Opposition Score			
VARIABLES	All Pitches		Fastballs		All Pitches		Fastballs	
Pitch Count	-0.048***	-0.048***	-0.009***	-0.009***	0.024***	0.024***	0.023***	0.023***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Pitch Count Squared	0.000***	0.000***	0.000***	0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Prev On Base (prev inning)	-0.075	-0.076	0.010	0.015	0.199***	0.199***	0.168***	0.170***
	(0.092)	(0.092)	(0.039)	(0.039)	(0.021)	(0.021)	(0.027)	(0.027)
Pitch Count * Prev On Base (prev inning)	0.001	0.001	-0.000	-0.000	-0.002***	-0.002***	-0.002***	-0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Prev At Bat (prev inning)	0.069*	0.085**	0.084***	0.099***	-0.279***	-0.279***	-0.293***	-0.292***
	(0.039)	(0.040)	(0.017)	(0.017)	(0.009)	(0.009)	(0.011)	(0.011)
Pitch Count * Prev At Bat (prev inning)	-0.000	-0.000	-0.001***	-0.001***	0.002***	0.002***	0.002***	0.002***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Balls	0.684***	0.684***	0.014***	0.014***	-0.006***	-0.006***	-0.006***	-0.006***
	(0.006)	(0.006)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
Strikes	-0.477***	-0.477***	0.412***	0.411***	-0.023***	-0.022***	-0.027***	-0.027***
	(0.007)	(0.007)	(0.003)	(0.003)	(0.002)	(0.001)	(0.002)	(0.002)
Times through order	-0.229***	-0.230***	-0.036***	-0.035***	0.503***	0.504***	0.495***	0.496***
	(0.016)	(0.016)	(0.007)	(0.007)	(0.004)	(0.004)	(0.005)	(0.005)
Constant	89.622***	89.622***	92.052***	92.051***	-0.492***	-0.492***	-0.483***	-0.482***
	(0.019)	(0.019)	(0.008)	(0.008)	(0.004)	(0.004)	(0.005)	(0.005)
Observations	1,150,287	1,150,287	678,316	678,316	1,155,136	1,155,136	678,475	678,475
Pitcher & Batter FE	YES	YES	YES	YES	YES	YES	YES	YES
Month, Ballpark & Year FE	NO	YES	NO	YES	NO	YES	NO	YES
R-squared	0.193	0.193	0.647	0.649	0.260	0.264	0.270	0.275

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A3: Including Lagged Inning Velocity	(1)	(2)	(3)	(4)
	Velocity			
VARIABLES	All Pitches		Fastballs	
Pitch Count	-0.016***	-0.016***	0.002***	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)
Pitch Count Squared	0.000***	0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Prev On Base (prev inning)	-0.013	-0.022	0.064*	0.055
	(0.088)	(0.088)	(0.037)	(0.037)
Pitch Count * Prev On Base (prev inning)	0.000	0.000	-0.001*	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Prev At Bat (prev inning)	0.096**	0.123***	0.154***	0.175***
	(0.039)	(0.039)	(0.016)	(0.016)
Pitch Count * Prev At Bat (prev inning)	-0.000	-0.000	-0.001***	-0.001***
	(0.001)	(0.001)	(0.000)	(0.000)
Balls	0.721***	0.721***	0.016***	0.017***
	(0.006)	(0.006)	(0.002)	(0.002)
Strikes	-0.394***	-0.394***	0.409***	0.409***
	(0.007)	(0.007)	(0.003)	(0.003)
Lagged Inning Velocity	0.361***	0.354***	0.233***	0.224***
	(0.003)	(0.003)	(0.001)	(0.001)
Times through order	-0.223***	-0.228***	0.036***	0.031***
	(0.016)	(0.016)	(0.007)	(0.007)
Constant	56.521***	57.192***	70.806***	71.642***
	(0.274)	(0.276)	(0.117)	(0.117)
Observations	1,035,694	1,035,694	594,485	594,485
Pitcher & Batter FE	YES	YES	YES	YES
Month, Ballpark & Year FE	NO	YES	NO	YES
R-squared	0.198	0.199	0.661	0.664

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A4: Limiting the timeframe over which we consider the effect of Batting / Getting on base

Inning restriction	Prev At Bat	Prev On Base	Prev At Bat (fastballs)	Prev On Base (fastballs)
1-7	0.057	-0.047	0.090***	0.026
1-6	0.084**	-0.057	0.080***	0.011
1-5	0.090**	-0.053	0.025	0.034
1-4	0.091*	0.119	-0.026	0.140***
1-3	0.187***	0.196	-0.032	0.218***
1-2	0.251***	0.119	-0.075**	-0.140
2-7	0.073*	-0.034	0.148***	0.045
2-6	0.091**	-0.038	0.146***	0.034
2-5	0.093**	-0.030	0.108***	0.060
2-4	0.082	0.159	0.090***	0.182***
3-6	0.117**	-0.158	0.176***	-0.054
4-6	0.204**	0.131	0.216***	-0.090

*** p<0.01, ** p<0.05, * p<0.1

Table A5: Placebo Test	(1)	(2)	(3)	(4)
	Velocity			
VARIABLES	All Pitches		Fastballs	
Pitch Count	-0.049***	-0.048***	-0.008***	-0.009***
	(0.001)	(0.001)	(0.000)	(0.000)
Pitch Count Squared	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Prev On Base (prev inning)	-0.062	-0.077	0.026	0.025
	(0.088)	(0.088)	(0.037)	(0.037)
Pitch Count * Prev On Base (prev inning)	0.001	0.001	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Prev At Bat (prev inning)	0.056	0.082**	0.082***	0.105***
	(0.038)	(0.038)	(0.016)	(0.016)
Pitch Count * Prev At Bat (prev inning)	-0.000	-0.000	-0.001***	-0.001***
	(0.001)	(0.001)	(0.000)	(0.000)
Prev At Bat (prev inning) FALSE	0.003	0.025	-0.024***	-0.001
	(0.016)	(0.016)	(0.007)	(0.007)
Prev On Base (prev inning) FALSE	0.013	0.008	0.022*	0.022*
	(0.031)	(0.031)	(0.013)	(0.013)
Balls	0.673***	0.673***	0.011***	0.012***
	(0.005)	(0.005)	(0.002)	(0.002)
Strikes	-0.474***	-0.474***	0.404***	0.403***
	(0.006)	(0.006)	(0.003)	(0.003)
Times through order	-0.230***	-0.237***	-0.040***	-0.039***
	(0.015)	(0.015)	(0.007)	(0.007)
Constant	89.556***	89.556***	92.004***	92.000***
	(0.018)	(0.018)	(0.007)	(0.007)
Test (p val)	0.177	0.142	0.000	0.000
Observations	1,285,788	1,285,788	757,414	757,414
Pitcher & Batter FE	YES	YES	YES	YES
Month, Ballpark & Year FE	NO	YES	NO	YES
R-squared	0.195	0.196	0.647	0.649

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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